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Exploring Online Learning Profiles of In-service Teachers in a Professional Development Course

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This study aimed to explore online learning profiles of in-service teachers in South Korea, focusing on video lecture and discussion activities. A total of 269 teachers took an online professional development course for 14 days, using an online learning platform from which web log data were collected. The data showed the frequency of participation and the initial participation time, which was closely related to procrastinating behaviors. A cluster analysis revealed three online learning profiles of in-service teachers: *procrastinating* (n=42), *passive interaction* (n=136), and *active learning* (n=91) clusters. The active learning cluster showed high-level participation in both video lecture and discussion activities from the beginning of the online course, whereas the procrastinating cluster was seldom engaged in learning activities for the first half of the learning period. The passive interaction cluster was actively engaged in watching video lectures from the beginning of the online course but passively participated in discussion activities. As a result, the active learning cluster outperformed the passive interaction cluster in learning achievements. The findings were discussed in regard to how to improve online learning environments through considering online learning profiles of in-service teachers.

Keywords: Distance education, Online learning profile, Time management, Teacher education

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Introduction

Without time and space constraints, online learning expands learning opportunities for everyone who wants to learn. Due to the characteristics of online learning, the number of teachers who have taken online professional development courses is on the rise in teacher education (Kim, Kim, & Yu, 2015). Online courses can be helpful for teachers who have to usually spend long time on working at school.

Despite the benefits of online learning, several studies have found that teachers have difficulties in online learning because of a shortage of interaction with other learners (Jeong, 2004; Kwon, Shin, & Shin, 2010). Although teachers who take online courses are aware that interaction is necessary for meaningful learning, they passively participate in interactive online activities. Studies about online learning suggest that interaction among learners plays an important role in learning performance and persistence in higher education (Park & Kim, 2011). In online professional development courses, teachers can have a deeper understanding of teaching and learning through sharing their knowledge and experience with other teachers.

In addition, teachers are likely to have difficulty in time management which is influential in completing an online course. As one of self-regulated learning strategies, time management skills can be crucial especially in teacher education because teachers are required to study in an online course as well as teach students at school. Moreover, online courses provide more autonomy in what and how to learn than face-to-face courses. The successful completion of an online course often depends on how efficiently teachers use their limited time. In Kwon, Shin, and Shin (2010)'s research, about 40 percent of Korean teachers pointed out the lack of learning time as an obstacle in taking online courses. For effective online professional development, instructional supports are necessary to help teachers to manage their own learning time.

In order to enhance interactive learning and help time management, learning analytics can be applied through monitoring online learning behaviors and timely providing adaptive instructional support. Learning analytics is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long & Siemens, 2011, p. 3). To apply learning analytics, web log data extracted from an online learning platform can be used as indicators of student behaviors regarding workload, learning patterns, participation, and interest (Park & Jo, 2014; Rha et al., 2017).

For adaptive instructional support, it is necessary to understand online learning behaviors that significantly influence learning achievements. In previous studies, a cluster analysis has been used to explore online learning profiles that consist of important learner behaviors, using web log data (Geri & Winer, 2015; Jo, Kim, & Yoon, 2014). The findings of online learning profiles can be used to categorize learners according to their learning behaviors (e.g., watching video lectures, writing discussion messages, taking quizzes) and to provide adaptive instructional supports that prevent dropping out and improve achievements.

The purpose of this study is to explore in-service teachers' online learning profiles in a professional development course, using web log data of video lectures and discussion boards. The learning profiles can be closely related to login frequency and learning achievements. Although previous studies investigated teachers' online learning behaviors, these studies tended to rely on surveys, which can be different from actual behaviors of learners (Levy & Ramim, 2012).

The Research questions of this study are as follows:

(1) What are online learning profiles of in-service teachers in regards to video lecture and discussion activities in an online professional development course?

(2) What are the relationships between online learning profiles and login frequency over time?

(3) What is the influence of online learning profiles on learning achievements?

Literature Review

Online learning activities

In online learning environments, learners can participate in diverse learning activities anytime and anywhere. Those activities mainly include watching videos, participating in online discussion, and other activities such as taking quizzes and submitting assignments (Alario-Hoyos et al., 2016; Hew, 2016). Because the course content is often provided in video format, recent studies indicate that learners spend a significant amount of time watching video lectures (Breslow et al., 2013; Kim et al., 2014).

Video is a largely-used resource for online learning, and its content is directly related to the course objective; thus, learning behaviors regarding video lectures are considered significant factors determining learners' success in the course. Geri and Winer (2015), for example, found that learners who viewed asynchronous video lectures were more successful than those who did not. Pursel et al. (2016) also reported an association between watching one more video per week and 1.1 percentage increase in a completion rate of a Massive Open Online Course (MOOC).

Besides viewing video lectures, participating in online discussion also serves as a strong predictor of learners' achievements. Previous studies have shown that active participation in online discussion can lead to high achievements and low dropout rates in online learning (Alstete & Beutell, 2004; Coetzee et al., 2014; Kizilcec et al., 2013). In a study where engagement types of online learners were classified into four groups – 'completing', 'auditing', 'disengaging', and 'sampling' – the first group students who completed the majority of the class assessments exhibited the highest level of participation in online discussion (Kizilcec et al., 2013). Coetzee et al. (2014) found that even just visiting the discussion page had a positive impact on the final grades.

Recently, a few studies attempted to compare video lecture with discussion activities in regard to learning achievements. For example, Koedinger et al. (2015) found that writing posts on a discussion board was more effective in learning achievements than watching videos and reading course materials. Michinov et al. (2011) also found that participation in online discussion had a mediating effect predicting low achievement of high procrastinators, but viewing video lectures didn't have such an effect. These studies indicate that participating in online discussion can be more important than watching video lectures. The two activities are different from each other in regard to the types of engagement for learning.

Chi and Wylie (2014) developed the ICAP framework to differentiate students' engagement behaviors into four categories: interactive, constructive, active, and passive learning. Based on a number of studies, the ICAP framework suggests that learning achievements will increase as the engagement behaviors move from passive towards interactive ones. Although the framework was developed on the basis of studies conducted in face-to-face learning environments, this framework can also be applied to online learning activities (Zhang, Lin, Zhan, & Ren, 2016); interactive learning in discussion forums can be more influential in knowledge acquisition than passively watching video lectures.

Time management in online learning

Considering the openness and flexibility of online learning environments, learners need to have self-discipline or self-control to stay on their learning trajectories and complete an online course (Song & Hill, 2007). Among various strategies to monitor and control one's learning process, time management skills are one of the most critical factors related to completion and achievement in online learning (Nawrot & Doucet, 2014). Song et al. (2004), for example, reported that time management strategies had a positive effect on participants' success in online learning. Nawrot and Doucet (2014) also found that high drop-out rates in MOOCs were closely associated with ineffective time management of learners.

Failing in time management for learning often leads to procrastination. Academic procrastination can be defined as the avoidance of studying and completing assignments down to the last second, which is usually accompanied by anxiety (Solomon & Rothblum, 1984). There is a negative correlation between procrastination and learning achievement (Ariely & Wertenbroch, 2002; Howell & Buro, 2009). Procrastination has a detrimental effect on meaningful learning because both the quality and quantity of learning become limited with lack of time (Rakes & Dunn, 2010). According to Wolters (2003), learners who showed chronical academic procrastination lacked using metacognitive strategies and self-regulation skills, which implies that adequate feedback and instructional support should be given to prevent learners’ procrastinating behaviors. Course Signals developed in Purdue University, for example, facilitated students' early participation and improved their grades by sending personal email reminders as well as a visualized traffic signal that showed individual learning process (Arnold & Pistilli, 2012).

Methods

Participants

Participants (n=269) in this study were in-service teachers who took an online course for professional development in South Korea. A total of 355 teachers registered the online professional development course, and 269 teachers completed the course. The data of teachers who did not complete the course were excluded from this study. Among the participants, there were 64 primary school teachers (23.8%) and 205 secondary school teachers (76.2%). The mean age was 37.56 years (*SD*=10.51).

Online course

The participants studied school administration for 14 days on an online learning platform. The course included 15 units each of which provided a 25-min video lecture. As shown in Figure 1, participants were expected to participate in discussion activities and watch video lectures. In addition, the online learning platform provided participants with information of their learning progress at a dashboard.

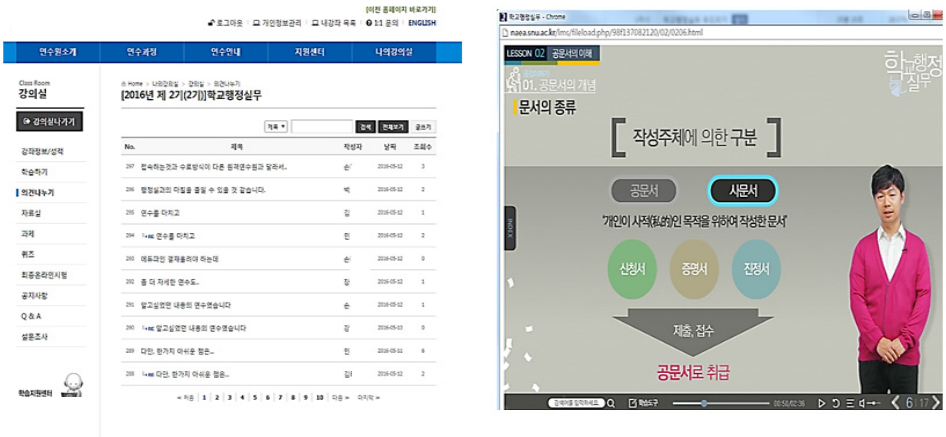

Figure 1. Online learning environments: discussion board (left) and video lecture (right)

To complete the course, participants should watch over 80% of the video lectures in 14 days. Evaluation categories included a written assignment (40 points) and an online multiple-choice test (40 points). In addition, participants should post at least four messages on discussion boards (20 points). They should get more than 60 points out of 100 points in order to complete the course. A tutor of the course sent reminder text messages to the participants before the deadline of the assignment and test. Although the sequence of video lectures was decided by an instructor, participants had autonomy in deciding when they would watch video lectures and write discussion messages within the learning period.

Data collection and analysis

From the online learning platform, this study collected web log data regarding the frequency of watching video lectures and posting discussion messages and the time of participation. Previous studies showed that interactive learning would be more effective in learning achievements than passive learning (Chi & Wylie, 2014; Koedinger et al., 2015). In addition, time management skills would play an important role in online learning (Nawrot & Doucet, 2014; Song et al., 2004). Based on these studies, we explored online learning profiles of in-service teachers with four variables: (1) initial posting of discussion messages, (2) posting frequency of discussion messages, (3) initial watching of video lectures, and (4) playback time of video lectures. The behavior of posting a discussion message indicates participation in interactive learning activities, whereas watching a video lecture is a kind of passive learning activities which do not require overtly doing a learning-related activity except receiving information (Chi & Wylie, 2014). The profiles of interactive and passive learning activities may be significantly associated with learning achievements. In addition, this study assumed that initial participation time was closely related to time management skills. Learners who lack time management skills tend to show academic procrastination, delaying learning tasks to the point at which they are unlikely to conduct the tasks successfully. Initial participation time can provide useful information about the tendency of procrastination in online learning.

Initial posting of discussion messages indicates the first day when participants posted a discussion message. To give earlier participation higher scores, we adjusted the first posting date scores inversely from 1 point (14th day) to 14 points (1st day). For example, if participants posted a discussion message on the first day out of the 14 days, we provided 14 points. If they posted a discussion message on the last day, we provided 1 point. The posting frequency is the total number of discussion messages posted by participants. Initial watching of video lectures means the first day when participants watched video lectures. The scores were calculated in the same method with the initial posting of the discussion messages. Playback time of video lectures is the sum of time to watch video lectures. The time was calculated with the web log data indicating when participants started and finished watching a video lecture. In addition to the four variables, we collected login frequency data in order to investigate the relationship between online learning profiles and login frequency over time. We counted how many times participants logged on the online learning platform per day from the first to the last day.

The learning achievement was measured with the scores of a written assignment and a multiple-choice test. The assignment was to write an official document which is used in the school administrative tasks, and the tutor evaluated the assignment based on the principles presented by the video lectures. The maximum score of the assignment was 40 points. The multiple-choice test consisted of 20 items measuring the understanding of school administration. Test items were developed by three subject-matter experts of the online course and automatically scored at the platform.

Table 1. Variables of online learning activities

Variables		Explanation
Interactive Activity	Initial posting of discussion messages	Assigned scores by the first day of posing a message on the discussion board
	Posting frequency of discussion messages	Number of messages on the discussion boards
Passive Activity	Initial watching of video lectures	Assigned scores by the first day of watching video lectures
	Playback time of video lectures	Sum of the time (hours) to watch video lectures
Login frequency		Number of login by learning date

To investigate online learning profiles of participants, a hierarchical cluster analysis was conducted with four variables in Table 1, using Ward's method. The number of clusters was determined by examining a dendrogram. According to Jain, Murty, and Flynn (1999), the clusters were classified based on the dendrogram representing the nested groups of patterns and similarity levels. After the cluster analysis, ANOVAs were carried out to find the differences of the clusters in regards to the four variables. To identify differences in login tendencies onto the platform among the clusters, we visualized and compared login frequencies of the clusters for the learning period. For a closer investigation of the login tendency, ANOVAs were conducted to examine the differences of clusters in login frequencies for the first 3 days and the last 3 days. Lastly, an ANOVA was conducted to investigate the differences of clusters in learning achievements.

Results

Online learning profiles of in-service teachers

Before conducting a cluster analysis, we carried out a correlation analysis to explore the relationships of four online learning variables and learning achievement. As shown in Table 2, initial posting of discussion messages had significant correlations with posting frequency of discussion messages (r=.47, p<.001) and initial watching of video lectures (r=.27, p<.001). In addition, learning achievement had positive correlations with initial posing of discussion messages (r=.13, p=.033) and posting frequency of discussion messages (r=.21, p=.001), but a negative correlation with playback time of video lectures (r = -.13, p=.028).

Table 2. Correlations among the variables

	1	2	3	4	5
1. Initial posting of discussion messages	1				
2. Posting frequency of discussion messages	.47**	1			
3. Initial watching of video lectures	.27**	.06	1		
4. Playback time of video lectures	.00	-.08	.06	1	
5. Learning achievement	.13*	.21**	-.01	-.13*	1

Note. $^{*}p$ <.05, $^{**}p$<.01

Three online learning profiles were identified from a cluster analysis with four online learning variables. There were 42 participants (15.61%) who were classified into the '*procrastinating*' cluster. As shown in Figure 2, this cluster had low scores in both initial posting of discussion messages and initial watching of video lectures. This cluster was named as the procrastinating cluster because the participants were seldom engaged in online learning activities at the beginning of the course and delayed their tasks to the last dates. The second cluster was named as the '*passive interaction'* cluster, which included 136 participants (50.56%). They showed lower participation in discussion activities when compared to watching video lectures. Participants in the passive interaction cluster might prefer watching video lectures individually to interacting with others in discussion boards. Lastly, there were 91 participants (33.83%) in the '*active learning'* cluster. In the cluster, participants were actively engaged in both video lecture and discussion activities from the beginning of the learning period. Particularly, they were more active in posting discussion messages than those in the other clusters.

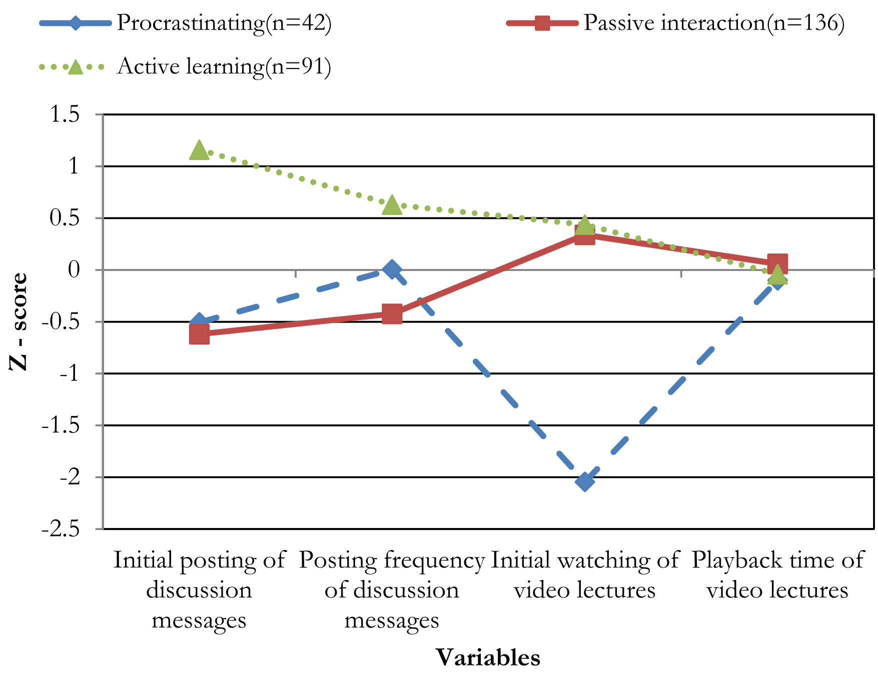

Figure 2. Online learning profiles of in-service teachers

Table 3. Differences of clusters in online learning activities

	Procrastinating (1, n=42) *M* (*SD*)	Passive interaction (2, n=136) *M* (*SD*)	Active learning (3, n=91) *M* (*SD*)	*F*	*p*	Post hoc test
Initial posting of discussion messages	2.29 (1.89)	1.85 (1.47)	8.58 (2.88)	298.33	<.001	3>1, 2
Posting frequency of discussion messages	3.88 (2.31)	2.74 (2.18)	5.55 (2.62)	38.82	<.001	3>1>2
Initial watching of video lectures	5.50 (2.33)	12.91 (1.32)	13.22 (1.14)	466.64	<.001	2, 3>1
Playback time of video lectures	3.22 (.42)	3.27 (.34)	3.24 (.23)	.51	.6	

ANOVAs were conducted to examine the differences of three clusters in online learning activities. As shown in Table 3, there were significant differences among the clusters in regards to initial posting of discussion messages, $F(2, 266)=298.33$, $p<.001$, posting frequency of discussion messages, $F(2, 266)=38.32$, $p<.001$, and initial watching of video lectures, $F(2, 266)=466.64$, $p<.001$. However, there was no significant difference in the playback time of video lectures, $F(2, 266)=.51$, $p=.6$. Post-hoc tests (Bonferroni) showed that the active learning cluster had higher scores in initial posting of discussion messages and posted more discussion messages than the other clusters (*ps*<.05). Although there was no significant difference between the procrastinating cluster and the passive interaction cluster in initial posting of discussion messages ($p=.737$), the former posted more discussion messages than the latter ($p=.019$). In addition, the active learning cluster and the passive interaction cluster had higher scores in initial watching of video lectures than the procrastinating cluster (*ps*<.05).

Login frequency over time

As presented in Figure 3, the active learning cluster and the passive interaction cluster constantly logged in the online learning platform from the beginning of the online course. In the procrastinating cluster, by contrast, participants seldom logged in the platform, but the login frequency largely increased at the end of the learning period. ANOVAs were conducted to compare the login frequency among the three clusters in the first three days and the last three days. There was a significant difference among the clusters in the first three days $F(2, 266)=38.78$, $p<.001$ (see Table 4). Post-hoc tests (Bonferroni) showed that the active learning cluster logged in more frequently than the passive interaction cluster ($p=.001$), and the passive interaction cluster had higher login frequency than the procrastinating cluster ($p<.001$). There was also a significant difference in the login frequency among the three clusters in the last three days, $F(2, 266)=13.54$, $p<.001$. Post-hoc tests showed that the procrastinating cluster and the passive interaction cluster logged in the online learning platform more frequently than the active learning cluster in the last three days ($ps<.05$).

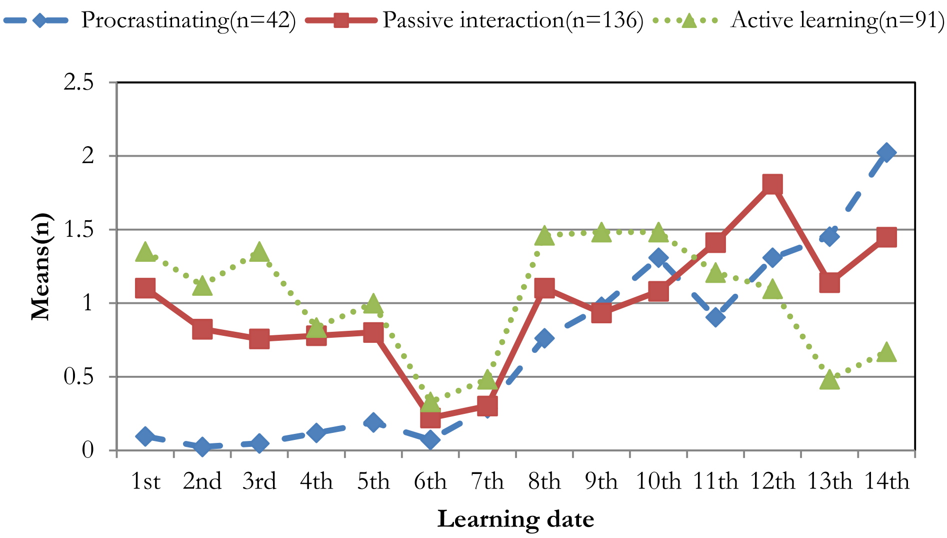

Figure 3. Login frequency by learning date

Table 4. Comparisons of login frequency by the first and last 3 days

	Procrastinating (1, n=42)	Passive interaction (2, n=136)	Active learning (3, n=91)	*F*	*p*	Post hoc test
	M (*SD*)	*M* (*SD*)	*M* (*SD*)			
Login frequency of the first 3 days	.17 (.48)	2.68 (2.29)	3.82 (2.59)	38.78	<.001	3>2>1
Login frequency of the last 3 days	4.79 (3.99)	4.40 (3.84)	2.25 (2.01)	13.54	<.001	1,2>3

Influence of online learning profiles on achievement

An ANOVA showed that online learning profiles significantly influenced learning achievement, $F(2, 266)=5.13$, $p=.006$. A post-hoc test (Bonferroni) indicated that the active learning cluster ($M=72.56$, $SD=4.90$) had higher learning achievement than the passive interaction cluster ($M=70.34$, $SD=5.41$), $p=.005$. However, there was no significant difference in learning achievement between the active learning cluster and the procrastinating cluster ($M=71.28$, $SD=4.53$), $p=.548$.

Discussion

This study intended to categorize in-service teachers' online learning behaviors in terms of passive and interactive learning activities and time management. This study also explored relationships between online learning profiles and login frequency and the influence of online learning profiles on learning achievement. This study found three meaningful clusters: procrastinating, passive interaction, and active learning clusters. In the procrastinating cluster, participants had a tendency to delay their tasks to the last dates of the online course. On the other hand, the active learning cluster constantly studied from the beginning of the online course and showed high-level participation in both video lecture and discussion activities. The passive interaction cluster was less engaged in posting discussion messages when compared to watching video lectures. At the beginning of the course, the active learning cluster logged in the online learning platform more than the procrastinating cluster, but the latter logged in the platform more than the former at the end of the course. In regard to learning achievement, the active learning cluster acquired higher scores than the passive interaction cluster. A correlation analysis also showed a positive relationship between the discussion activity and learning achievements in the online professional development course.

This study supported that interactive learning activities play a critical role in getting higher learning achievement. The finding of this study is consistent with the ICAP framework in which interactive activities are more effective in knowledge acquisition than passive activities (Chi & Wylie, 2014). Koedinger et al. (2015) also found that acquiring declarative information by watching video lectures and reading learning materials was less effective than participating in interactive activities such as writing a discussion message. Interactive activities in online learning can help to gain knowledge by facilitating critical thinking and knowledge building (Ramos & Yudko, 2008).

This study also showed the importance of time management skills. The later learners participate in discussion activities, the fewer opportunities to interact with others are given to learners (Michinov et al., 2011). In this study, initial posting of discussion messages was significantly associated with posting frequency of discussion messages. Learners with academic procrastination might lack knowledge of metacognitive strategies and self-regulation skills (Wolters, 2003). Therefore, it is necessary to provide instructional supports to prevent learning delays and facilitate active interaction. For example, an instructor can help learners to reflect on their online discussion activities by providing feedback. Cho et al. (2015) found that undergraduates improved their online discussion activities through reflecting on feedback that visualized participation time, discussion frequency, interaction with group members, and message types. The visualized feedback might help learners to monitor and regulate their online learning behaviors.

Lastly, the findings of this study imply the need of adaptive instructional supports based on online learning profiles. It is necessary to check regularly online learning profiles and to provide timely assistance to the learners who procrastinate or passively participate in interaction. Using learning analytics, for instance, a dashboard can provide learners with valuable information and guidance on learning process (Rha et al., 2017). Auvinen, Hakulinen, and Malmi (2015) suggested that dashboards allow an instructor to effectively monitor and support learners' online learning behaviors, visualize learners' knowledge levels, send notifications to at-risk learners, and facilitate learners' reflection on their online learning process. Dashboards can be much helpful for adult learners like in-service teachers who should efficiently manage their limited time for online learning.

Despite the meaningful findings of this study, careful attention should be paid when applying the findings to other online learning contexts. In this study, online learning was conducted in a short period (14 days) for in-service teachers. In order to generalize the findings, further research should be conducted with diverse learners in a longer period of online learning. In addition, this study used only four variables in analyzing online learning profiles. Although the variables are closely related to important online learning behaviors, future research needs to include more diverse variables such as demographic information, self-reported survey results, and other learning process data so as to increase the validity of online learning profiles. These efforts will enhance adaptive instructional support in online professional development courses.

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